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14. ABSTRACT
Warfighters have benefited significantly from the enormous advances in digital technology over the past several decades. In contrast, too little of the considerable progress in neuroscience has been applied to improving warfighter performance. We believe this reflects the absence of digital technology that can help bridge the gap between neuroscience and digital systems. We believe this gap might be filled by constructing a computational model of the neuro-cognitive activity of the warfighter. We propose that such a model could be created by

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Neurometric Modeling: Computational Modeling of Individual Brains

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Warfighters have benefited significantly from the enormous advances in digital technology over the past several decades. In contrast, too little of the considerable progress in neuroscience has been applied to improving warfighter performance. We believe this reflects the absence of digital technology that can help bridge the gap between neuroscience and digital systems. We believe this gap might be filled by constructing a computational model of the neuro-cognitive activity of the warfighter. We propose that such a model could be created by algorithms applied to measurements of brain activity obtained using functional MRI. Algorithmic processing of these measurements can exploit a variety of statistical machine learning methods to synthesize a new kind of neuro-cognitive model, which we call neurometric models. These executable models could be incorporated into a number of applications for assessing and improving mental performance, including battlefield training and treatment of disorders such as PTSD. The long term goal is to enable systems that can better adapt to the warfighter in real-time due to model-generated hypotheses about the individual's neuro-cognitive state.

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Number of Presentations: 0.00

Non Peer-Reviewed Conference Proceeding publications (other than abstracts):

Number of Non Peer-Reviewed Conference Proceeding publications (other than abstracts): 0

Peer-Reviewed Conference Proceeding publications (other than abstracts):

Number of Peer-Reviewed Conference Proceeding publications (other than abstracts): 0

(d) Manuscripts

Number of Manuscripts: 0.00

Patents Submitted

Patents Awarded

Awards

Graduate Students

NAME	PERCENT_SUPPORTED
Padmini RAJAGOPALAN	0.13
Aditya Rawal	0.13
FTE Equivalent:	**0.26**
Total Number:	**2**

Names of Post Doctorates

NAME	PERCENT_SUPPORTED
FTE Equivalent:	
Total Number:	

Names of Faculty Supported

NAME	PERCENT_SUPPORTED	National Academy Member
David Ress	0.03	No
Risto Miikkulainen	0.03	No
FTE Equivalent:	**0.06**	
Total Number:	**2**	

Names of Under Graduate students supported

NAME	PERCENT_SUPPORTED
Evan Luther	0.13
FTE Equivalent:	**0.13**
Total Number:	**1**

Student Metrics

This section only applies to graduating undergraduates supported by this agreement in this reporting period

The number of undergraduates funded by this agreement who graduated during this period: 0.00

The number of undergraduates funded by this agreement who graduated during this period with a degree in science, mathematics, engineering, or technology fields:...... 0.00

The number of undergraduates funded by your agreement who graduated during this period and will continue to pursue a graduate or Ph.D. degree in science, mathematics, engineering, or technology fields:...... 0.00

Number of graduating undergraduates who achieved a 3.5 GPA to 4.0 (4.0 max scale):...... 0.00

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Names of Personnel receiving masters degrees

NAME
Total Number:

Names of personnel receiving PHDs

NAME
Total Number:

Names of other research staff

NAME	PERCENT_SUPPORTED	
Bruce Naylor	0.13	No
FTE Equivalent:	**0.13**	
Total Number:	**1**	

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Scientific Progress

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Technology Transfer

Neurometric Modeling

Computational Modeling of Individual Brains

Abstract

*Warfighters have benefited significantly from the enormous advances in digital technology over the past several decades. In contrast, too little of the considerable progress in neuroscience has been applied to improving warfighter performance. We believe this reflects the absence of digital technology that can help bridge the gap between neuroscience and digital systems. We believe this gap might be filled by constructing a computational model of the neuro-cognitive activity of the warfighter. We propose that such a model could be created by algorithms applied to measurements of brain activity obtained using functional MRI. Algorithmic processing of these measurements can exploit a variety of statistical machine learning methods to synthesize a new kind of neuro-cognitive model, which we call **neurometric models**. These executable models could be incorporated into a number of applications for assessing and improving mental performance, including battlefield training and treatment of disorders such as PTSD. The long term goal is to enable systems that can better adapt to the warfighter in real-time due to model-generated hypotheses about the individual's neuro-cognitive state.*

Introduction

While fMRI has been used for research purposes for over a decade and a half, the analysis of the data produced by this imaging technology has been primarily for the benefit of neuro-cognitive researchers who are conducting scientific enquiry into how all brains work in general. It has not been applied in any significant degree to improving performance of the individual. The traditional scientific goals has lead to an anatomically oriented approach: attempts are made to determine what functionality individual regions of the brain provide. This requires a high degree of precision that current fMRI technology has difficulty providing, and is compounded by the variation among individuals.

Whereas this standard approach uses anatomy as the fundamental frame of reference, we will take a different approach, one that instead utilizes computation as the fundamental frame of reference. Our proposed schema will transform measurements of brain activity algorithmically and automatically into an abstract neuro-cognitive computational model of simple tasks being performed by individuals. We call such measurement-driven models, ***Neurometric Models***.

While computational neuroscience has been pursuing modeling of the brain for several decades, many of these efforts have been 1) anatomically based, 2) concerned with brains in general, 3) are spatially oriented, and 4) have built software models manually. In contrast, our approach will be 1) computationally based, 2) targets modeling a given individual's brain, 3) will emphasize the temporal domain, and 4) is synthesized automatically. This last point is critical given our goal of modeling individual brains, because the cost of manual model construction would most likely be prohibitive otherwise.

Our approach builds on recent work that uses pattern recognition algorithms applied to fMRI images to identify brain states. The brain states will be limited to those that occur while an individual is performing a task of interest, such as those taught using virtual-world based training systems. No attempt will be made to model brain functionality in general, which is presently far too ambitious. The specific anatomical distribution of brain activity will be captured by a pattern recognizer that is created using artificial neural networks trained on the fMRI data.

Experimental Design

For our stimuli, we used 3D virtual environments like those used in training simulators. Each stimulus was created using Unreal Development Kit 3.0, which is a combination authoring and rendering system used for commercial game and simulation products. Using virtual environments, as opposed to photographs or drawings, exploits the brain's natural design for operating in a 3D environment. Compared to video, virtual environments enable interactivity that is needed for performing a task. Virtual environments also provide a high degree of control over the design of the stimuli, as well as complete knowledge of its contents.

For this study, we created a small virtual town suggestive of those encountered in current Middle East combat zones. We introduced into this environment three categories of characters: soldiers, insurgents, and indigenous civilians (see below). The view for the virtual camera was chosen to be 1st person, as is typical of most training systems, in order to create the impression of being an agent in the environment. We created a very simple scenario suggestive of searching for snipers. We alternated between moving the viewer through pasts of the town in which there were no characters present (searching), and stopping at certain locations where characters appeared in varying combinations (encountering). The characters and the viewer were always exhibiting slight motion, so at no time was there static imagery.

We chose a mixed block design for our initial experiments. In many examples of block designs for cognitive neuroscience, there is an alternation between presenting the desired stimulus and displaying a blank screen (perhaps with a cross-hair to give the subject something to focus on). This technique maximizes the contrast when a single simple task or stimulus is to be quantified. In our case, such a radical alternation would be alien to the example application of training. Rather, we chose to always maintain the experience of being in the virtual world with continuous motion. Our use of block design alternates between the two modes: 1) moving through the town with no characters visible (searching), 2) remaining in a single location in the town with a mix of characters directly in front of the viewer (encountering). Each of the two phases was 15 seconds long, for a total of 30 seconds for each character combination. The nature of the encounters varied from block to block, but the retention of a block design structure was chosen to enable selection of responsive voxels in the fMRI data.

1 out of 16 combinations used for CONSTANT stimulus

We used two stimulus conditions. One was designed to test whether the neural network could be trained to count the number of characters in the scene when all the characters were of a single type: either soldiers or insurgents. The second was designed to evoke a variable level of threat by presenting a mix of soldiers, insurgents and civilians. The number of characters in the first condition varied from 1-6, where as the total number of characters in this second condition was held constant at 6 in order to control for human vision processing that correlated only with the number of characters. We refer to the first condition as VARYING (because of the varying number of characters) and the second as CONSTANT (because of the constant number of characters). For VARYING, all 1 to 6 possible cases were present twice in random order within a single scan. For CONSTANT, the number of soldiers ranged from 0 to 3, and similarly for the number of insurgents. The number of civilians = 6 – (# soldiers + # insurgents). With 0:3 X 0:3 possible mixes, there were a total of 16 combinations. The order in which the combinations was presented to the subject were always a random permutation.

Data Acquisition

The fMRI data was obtained using a GE Signa 3.0T scanner, located at the U. of Texas at Austin Imaging Research Center. Sessions began by obtaining a T1-wieghted anatomy on the same slice prescription as the fMRI data using a SPGR sequence. The fMRI data was acquired using a T2*-sensitive EPI sequence. Image quality was improved by using an 8-channel head-coil array combined with a GRAPPA parallel imaging scheme. The GRAPPA speed-up factor was 3:1 to obtain whole-brain volumes of 36-44 slices every 2 seconds, with a cubic voxel size of 2.5mm per side. The first 12 seconds of data was discarded to mitigate transient effects. The data was converted to a per voxel time series format. This data was then motion corrected, using a rigid body transformation, first within each scan and then between successive scans. Finally, a timing correction was applied to compensate for the interleaved slice acquisition.

We then selected a relatively small subset of the voxels to use as inputs to the neural network (a.k.a. feature selection). This selection was based on the periodic nature of the block design. Responses to a periodic stimulation, regardless of its form, will show power only at the fundamental and harmonics of the stimulation. We performed a harmonic analysis in which we summed the time-series power present at the fundamental and harmonics 2—4. Those voxels with a fractional power greater than a particular threshold were selected for the next stage of processing. The power threshold was chosen to select a fixed number of voxels, typically ~3000.

Results

Both of our stimulus conditions produced statistically significant activity in a variety of brain regions. Similar patterns of activity were also obtained by more conventional forms of analysis such as correlation with a best-fit sinusoid at the block-stimulus frequency. We found clusters of activity in frontal lobes, posterior parietal lobes, and regions of ventral occipital cortex often associated with object selectivity.

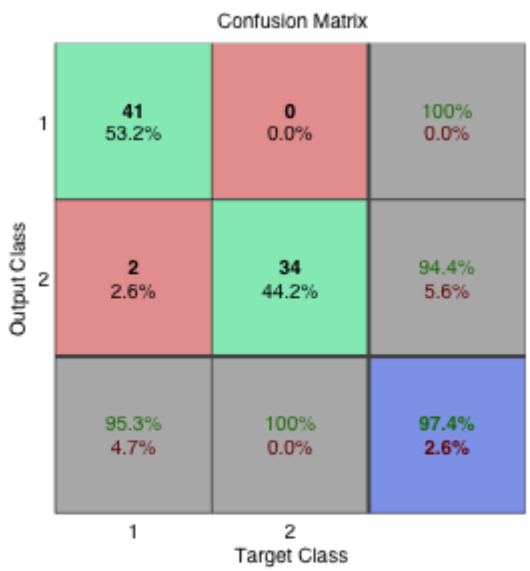
In this pilot study, our objective was to assess the viability of using neural networks (NN) to identify which brain activation patterns were indicative of certain simple characteristics of a dynamic virtual world. To our knowledge, this has never been done before. As noted above, we targeted two conditions: counting the number of characters and assessing threat level. In addition, mostly as a sanity check, we built NNs to distinguish between scenes of the town with and without characters in it. Because we selected voxels based on their correlation to alternating between these two cases, this presented a best case scenario for NNs. We used Matlab 2009 64-bit with the Neural Network Toolbox running on Linux OS for all of our results.

For this study, we restricted the class of NN to the feed-forward variety (the most common). These have a fixed structure characterized by a) the number of layers, b) the number of nodes in each layer, and c) the transfer function for each layer. Given an instance of this fixed structure, chosen from an endless number of possible such structures, the only variable components of the network are the weights at each node in the network. It is the adjustment of these weights to fit the example data that constitutes the “learning” process. This is a mathematical optimization problem, which like essentially all such problems, does not succumb to a direct solution. Rather an iterative search must be perform over the space of all possible weights. The search is guided by measuring the error between the network’s current output and the target output, which is given as part of the training set. The process gradually minimizes this error by traveling along the surface of the error function in a direction that reduces the error. However, the error function most always has many local minima into which the process will become trapped, so some additional element needs to be introduced to find the best local minima from a set of such. While simulated annealing is a general approach to this kind of problem, it is not provided by the NN Toolbox. Instead, we run the process multiple times, starting each run with a different set of randomly chosen initial weights. We then evaluate the goodness of each generated network using the validation set and keep the best one. As a basis of comparison, we calculate the average performance for the NN structure that yielded the best performance. In addition to classification, we also trained a network to give a continuous value output between 0-6 for counting characters. The performance for this kind of regression is given by an R-Value, where R = 1.0 is comparable to 100% correct. This is keeping with our plans to build a multi-dimensional representation of neuro-state-space.

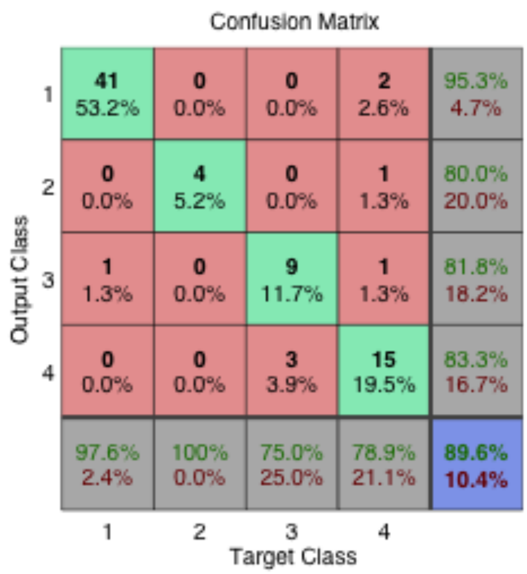
Here is a table of the results. Note the improvement from Subject A to the subsequence two subjects who where scanned several months after Subject A. This reflects our improvement of the fMRI protocol and data-processing.

	Counting Best	Counting Average	Threat-level Best	Threat-level Average	Continuous R-value
Subject A	95%	80%	90%	75%	.94
Subject B	100%	96%	94%	87%	1.0
Subject C	100%	96%	95%	85%	1.0
Chance	14%	14%	25%	25%	----

Table 1

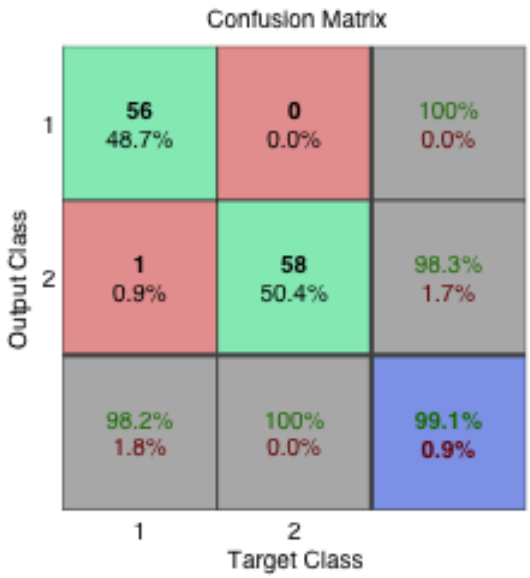


CONSTANT A: Characters Yes/No

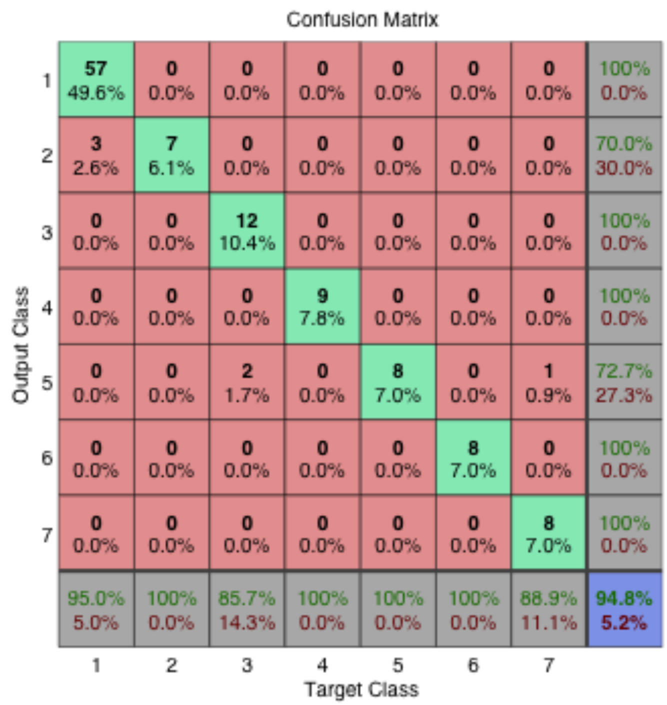


CONSTANT A: Threat level

A more detailed graphical presentation of the best data for subject A is shown above as a “confusion matrix”. A confusion matrix is used to display the effectiveness of solving classification problems. It shows for each classification on test inputs, which classification was assigned to it by the NN. With a perfect classifier, only the diagonal elements would contain counts of inputs. For example, in the VARYING A: Counting, the Target class # = # characters-1. Column 3 shows that 12 inputs of brain volumes, sampled when 2 characters were presented, were classified correctly, while 2 where misclassified as 4 characters, resulting in a 85.7% success rate (bottom row). The lower right element shows the overall performance of 94.8%.

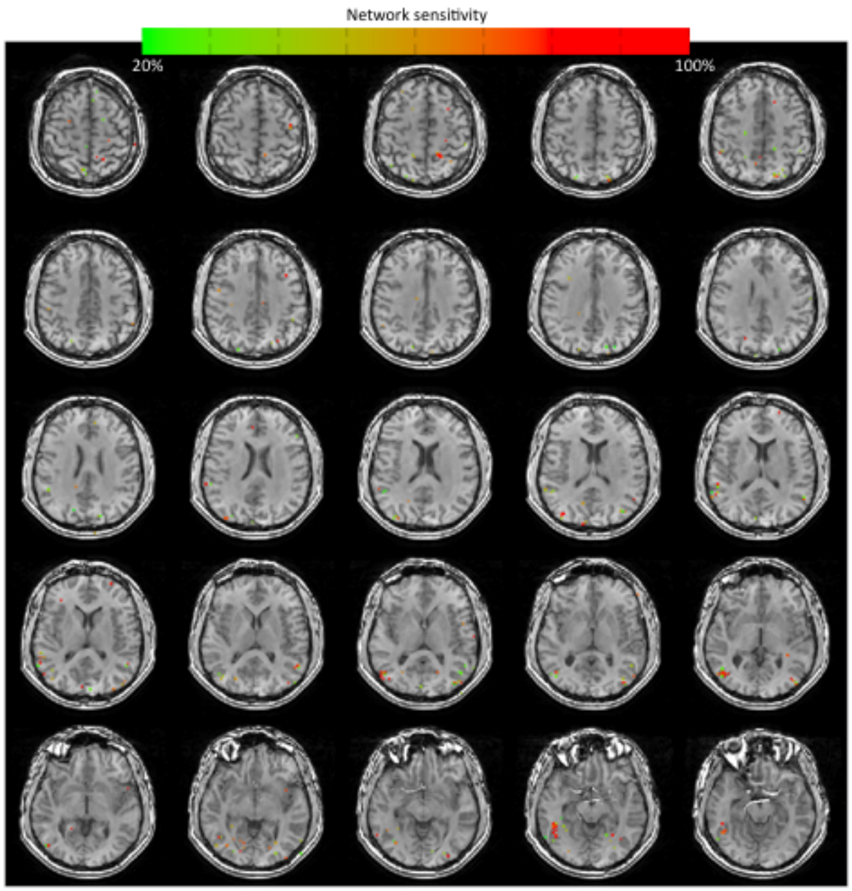


VARYING A: Characters Yes/No



VARYING A: Counting

For the VARIABLE condition, we also performed a sensitivity analysis as a means to estimate which of the input voxel time series most strongly influenced the outputs of the NN. Starting from the mean input state of the system, each input was perturbed by a small amount, the effect of the perturbation upon the output state was noted. This process was repeated for all input voxels. These sensitivity values were then normalized to their observed maximum across voxels, and the results are visualized below (next page). Only those voxels with sensitivities >10% are shown. Note that the network is very selective: only ~300 of the original 2800 voxel time series are given a weight >10%. Note also that these highly-weighted voxels occur exclusively in the gray matter of the brain. Finally, we observe that the majority of the highly weighted voxels are clustered in ventral occipital regions that are probably part of object-selective visual cortex, and in posterior parietal regions that probably have visual attention and association. It is also worth noting that the NN gave little weight to any frontal brain regions. Similar results were observed in Subject B, except there was less activation of posterior parietal regions. Thus, this analysis demonstrates the efficacy of NNs in discerning task-or-stimulus-relevant fMRI inputs, and provides us a means to relate these associations back to individual brain anatomy.



Sensitivity analysis results for Subject A

Discussion

The performance of the classifiers when compared to chance are excellent (see Table 1). The performance of 100% for counting, both for classification and regression, on more recent subjects is extremely encouraging. The better performance for Counting than Threat-level probably reflects the fact that assigning counting categories to stimuli is objective and that counting is a low-level cognitive activity. For threat level, the assignment was only quasi-objective, being based counting the number of friends vs. foes while the total number of characters was held constant.

Our approach to sensitivity analysis as applied to multivariate/voxel pattern analysis (MVPA) is, as far as we know, novel. It could prove to be an important new technique for characterizing which regions of the brain contribute the most to particular cognitive processing. It underscores the importance of using whole brain data rather than regions of interest. Indeed, the technique tell us which regions are the most relevant to the cognitive computations. The technique could also be used as part of the feature selection process by iteratively using the sensitivity to select voxels for subsequence construction of NNs.

To summarize, we have demonstrated the following:

1) Virtual Worlds like those used in military training can be used effectively as fMRI stimulus
2) Neural Networks can be constructed that can reliably identify brain activation patterns distinguishing the number of characters in the scene.
3) A variety of mixes of Soldiers, Terrorists and Civilians can be classified reliably into threat level by an NN.